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Analysis of Factors Contributing to Hit-and-Run Crashes Involved with Improper Driving Behaviors

Bei Zhou[a]*, Arash M. Roshandeh[b], Shengrui Zhang[a], Zhuanglin Ma[a]

[a]Shcool of Highway, Chang'an University, South 2nd Ring Road, Xi'an 710064, China
[b]Traffic Control Center at City of Alpharetta, 1790 Hembree Road, Alpharetta, GA 30009, USA

Abstract

Hit-and-run crashes are accidents where drivers of striking vehicles fail to stop after crashes. Without helping victims or reporting accidents to associated authorities could increase the likelihood of serious injuries and even fatalities. In order to reduce hit-and-run crashes, it is important to understand factors contributing to decisions of fleeing crash scenes. In current study, various factors which could affect occurrences of hit-and-run crashes were thoroughly investigated against six different improper driving behaviors. Logistic regression models were established to facilitate the analysis. Police-reported crash data within Cook County, Illinois, USA between 2004 and 2012 were used in this study. The results showed that variables contributing to hit-and-run crashes varied for different improper driving behaviors. Among six established models, "following too closely" and "distraction by phone" models had most statistically significant variables. This study also concluded that following variables would increase the likelihood of hit-and-run crashes in at least one model: multiple vehicle crash, weekend, population of 2,500 – 5,000, population of 5,000 – 10,000, national highway system, traffic signal, yield sign, shoulder, darkness, and less than three lanes. The results of current study could offer important insights for reducing hit-and-run crashes in both planning and operational levels.

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Keywords: hit-and-run; logistic regression model; odds ratio; traffic safety; improper driving behaviors

1. Introduction

Injuries and fatalities caused by traffic accidents has been acknowledged as a serious threat to human lives around the world. According to World Health Organization [15], almost 1.24 million people lose their lives as a result of

* Corresponding author. Tel.: +86-029-82334893; fax: +86-029-82334893.
E-mail address: bzhou2007@gmail.com

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traffic accidents each year. In addition, 20 to 50 million people are subject to non-fatal injuries. Although traffic accidents have diverse categories, hit-and-run crashes are among the most dangerous ones. Hit-and-run crashes refer to accidents where drivers of striking vehicles directly leave the scenes without helping victims or reporting accidents to relevant authorities. Hit-and-run behaviors could significantly increase the probability of severe injuries and even fatalities due to delays in emergency medical services.

Although hit-and-run is considered as a severe crime by most law enforcements and drivers have to face major crime charges if they were caught fleeing the scenes, hit-and-run crashes rate remains increases in many major cities. According to National Highway Traffic Safety Administration [9], fatalities caused by hit-and-run crashes experienced a 13.7% increase, from 1,274 in 2009 to 1,449 in 2011. It should be noted that overall deaths in traffic decreased by 4.5% during the same time period. This raises an urgent question for both state and local transportation agencies: how to bring down occurrences of hit-and-run crashes? In order to answer that, factors contributing to hit-and-run crashes need to be thoroughly analyzed. Nevertheless, only a few studies have been conducted to analyze factors associated with hit-and-run behaviors. Most of these studies focused on factors such as number of vehicles involved in a crash, road classification, traffic control devices, time and location of the crash, roadway profile and so on. Very few of them paid attention to driving behaviors of hit-and-run drivers.

The current study aimed at contributing to existing literature by exploring the association of different factors with hit-and-run crashes. In addition to comprehensive analysis of factors explored by previous studies, improper driving behaviors were also included. Six types of improper driving behaviors were considered in present study: i) drivers disregard road marking; ii) drivers get distracted due to using cell phone; iii) drivers get distracted due to chatting with passengers; iv) drivers get distracted from outside of vehicle (people, places or things of interest alongside the road); v) drivers follow too closely to the leading vehicle; vi) drivers take an improper overtaking.

The rest of this paper is organized as follows. Previous studies related to this topic were firstly reviewed. Next, data used for current study was described, followed by an overview of the logistic regression model developed for current study. Then, results of the calibrated logistic model were discussed in details. The last section presented conclusions and recommendations for future study.

2. Related work

Identifying factors contributing to hit-and-run crashes has attracted various researchers from diverse fields. Previous studies have examined the relationship of different factors to hit-and-run behaviors, including roadway factors, vehicle factors, drivers' characteristics, environmental factors, crash attributes and so on.

Solnick and Hemenway [12] pointed out that drivers were more likely to flee crash scenes if victims were between 16 and 25 years old and crash happened in an urban area, in summer or on weekends. A study performed at Singapore [13] used a logistic regression model to identify factors associated with the occurrences of hit-and-run crashes. It was found that drivers could be more likely to flee scenes if crashes happened near shop house; on straight road; involved two vehicles; and when the driver was a male, and aged between 45 and 69. In addition, it was also pointed out that crashes involving right turn and occurring on undivided road were less likely to be hit-and-run crashes. Kim et al. [7] applied rough set analysis combined with logistic regression model to identify factors affecting hit-and-run crashes in Hawaii. Both human factors and roadway characteristics were taken into consideration. They also recommended certain suggestions to reduce hit-and-run crashes. With regard to pedestrian fatalities due to hit-and run, Macleod et al. [8] utilized data on vehicle-pedestrian fatal crashes to establish a logistic regression model. It was claimed that early morning, poor lighting, and weekends could increase the probability of hit-and-run. Alcohol usage and invalid driving license had a significant impact on hit-and-run behaviors. Aidoo et al. [1] also examined pedestrian hit-and-run crashes based on a binary logistic regression model. The results indicated that unclear weather, nighttime, flat road without medians and intersections played vital roles in hit-and-run crashes involving pedestrians. Recently, Zhang et al. [16] conducted a comprehensive study regarding factors contributing to hit-and-run crashes in China. This study found out that crashes involved pedestrians, poor lighting conditions, male drivers without valid driving licenses, drivers with inadequate driving experience were more likely to be hit-and-run crashes.

Driving behaviors also have important influences on traffic safety. Improper driving behavior could increase the likelihood of crash occurrence. Greenberg et al. [5] evaluated impact of in-vehicle tasks on traffic safety based on driving simulator. Driving performances, such as lane violations, following distance and heading error were tested. It was pointed out that poor driving performance had adverse impacts on traffic safety. Most common drivers' distraction factor is using a cell phone [2,4,10]. It was found that drivers using cell phone while driving were more likely to run a stop sign or red light [3].

3. Data collection and processing

Dataset of the current study are police-reported crashes within Cook County in Illinois, USA, between years 2004 and 2012. Among several variables, one of them shows whether the crash was hit-and-run. Furthermore, there is a column showing the improper driving behavior which would be determined by police at the crash location. With that, the current study intends to find out the contribution factor of different variables on hit-and-run crashes if the improper driving behavior would be any of the following ones: i) disregard road marking; ii) distracted by phone; iii) distracted by passenger; iv) distracted by outside of vehicle (people, places or things of interest alongside the road); v) follow too close to the leading vehicle; and vi) improper overtaking/passing.

As such, the existing large dataset was firstly filtered out for each of the 6 above mentioned conditions which would be used separately in the analysis. In order to keep consistency among different analysis scenarios, 14,619 observations were used to run each model. Table 1 presented different variables and the corresponding distribution percentage of hit-and run crashes in dataset.

4. Methodology

The dependent variable in this study, hit-and-run, is a binary variable. As such, logistic regression is a suitable technique for modeling due to its ability for predicting a binary dependent variable as a function of independent variables. In traffic safety related studies, logistic regression model is widely used and has been proved to be reliable and efficient when the dependent variable is dichotomous [14]. With regard to current study, the logit is the natural logarithm of likelihood ratio, that the dependent variable (hit-and-run or non-hit-and-run) is 1, such that

$$Y = LOGIT(P) = LN(\frac{P(Y=1)}{1-P(Y=1)}) = \sum_{i=1}^{n} b_i X_i \tag{1}$$

where β_i denotes the vector of parameters estimated for corresponding independent variables X_i. Based on above equation, it can be derived that when independent variable X_i increases by one unit and all other variables remain the same, the odds increased by a factor $EXP^{\beta i}$. The factor $EXP^{\beta i}$ is called odds ratio (OR) and varies from zero to positive infinity. It could be used to denote the relative change in likelihood of drivers fleeing crash scenes with respect to one unit increase in corresponding independent variable. OR provides information about which independent variable has the most significant effect on hit-and-run behaviors.

In order to establish the logistic regression model, it is crucial to pre-select variables which are expected to affect hit-and-run behaviors. As mentioned in "Data collection and processing" section, 19 variables from 14 categories were separately examined for 6 different improper driving behaviors. To avoid the perfect multicollinearity problem, for each category, one variable was used as the reference case. For rest of variables in the category, the odds ratio against reference case was used to estimate the effect of variable. For example, for number of vehicles, single vehicle crash was used as reference case, and odds ratio of multiple vehicle crash could indicate the effect of multiple vehicle crash on hit-and-run relative to single vehicle crash. Please refer to table 3 and 4 for reference cases selected in each category.

Table. 1 Variables description and the corresponding distribution percentage of hit-and run crashes in dataset

Variables		Distribution percentage (%)					
Category	Description	disregard road	distracted	distracted by	distracted by outside	follow too close to the leading	improper overtaking/

		marking	by phone	passenger	of vehicle	vehicle	passing
Number of vehicles	Multiple vehicle crashes (1 if crash occurred between multiple vehicles, 0 otherwise)	23.8	22.9	14.0	17.1	25.9	43.2
Day of week	Weekend (1 if crash on weekend, 0 otherwise)	16.6	14.9	12.7	13.5	15.6	20.2
Time of day	AM peak (1 if crash occurred between 7am -9am; 0 otherwise)	12.4	12.7	12.0	12.5	13.6	16.8
	PM peak (1 if crash occurred between 4pm -6pm; 0 otherwise)	15.5	15.4	12.1	13.2	15.4	20.1
Population of area	2,500–5,000 (1 if crash occurred at the area with 2,500–5,000 population; 0 otherwise)	13.5	11.8	11.6	11.6	11.6	11.7
	5,000–10,000 (1 if crash occurred at the area with 5,000–10,000 population; 0 otherwise)	13.5	11.8	11.4	12.0	11.6	12.2
Crash Severity	Injury (1 if crash severity is injury; 0 otherwise)	15.5	14.0	12.2	13.7	13.4	14.0
Class of trafficway	Urban road (1 if crash occurred on urban roadway; 0 otherwise)	27.9	25.1	15.0	19.0	24.9	42.2
National highway	NHS (1 if crash occurred on NHS road; 0 otherwise)	19.6	16.7	12.4	14.5	18.2	23.5
Traffic control device	Traffic signal (1 if traffic control device is traffic signal; 0 otherwise)	13.5	17.6	12.4	13.4	17.2	19.8
	Failed to yield (1 if driver failed to yield; 0 otherwise)	11.4	11.4	11.4	11.6	11.4	11.4
Road surface	Wet (1 if crash occurred on wet roadway; 0 otherwise)	12.4	12.7	12.0	11.9	13.6	14.8
	Sand (1 if crash occurred on sandy roadway; 0 otherwise)	12.1	11.4	11.4	11.4	11.4	12.1
Crash location	Shoulders (1 if crash occurred on shoulders; 0 otherwise)	12.4	11.8	11.4	11.4	11.8	12.2
	Work zone (1 if crash occurred at work zone; 0 otherwise)	11.4	11.4	11.4	11.4	11.4	11.5
Light condition	Darkness lighted (1 if dark and lighted roadway; 0 otherwise)	17.6	18.0	12.9	14.2	16.4	21.8
Number of lanes	Number lanes < 3 (1 if crash occurred on roadway with less than 3 lanes; 0 otherwise)	16.6	20.2	13.0	15.1	16.5	24.8
Alignment	Curve (1 if crash occurred on curve roadway; 0 otherwise)	12.4	11.8	11.5	11.7	11.6	12.1
Median type	Divided (1 if crash occurred on divided roadway; 0 otherwise)	19.6	16.7	12.9	14.5	19.3	26.5

5. Results and discussions

The current study applied NLOGIT Version (4.0.1) for logistic regression analysis regarding different scenarios. Without losing of generality, all possible variables which might affect hit-and-run behaviors were kept in the model. Table 3 and Table 4 presented p-values and odds ratios for all variables, respectively. The results suggested that models fitted the whole data very well, with relatively large McFadden pseudo R^2 values and small p-values.

McFadden pseudo R^2 statistics, number of statistically significant ($p<=0.05$) or marginally significant ($p<=0.1$) variables for each model could be found in Table 2.

Table. 2 Fitness and number of statistically significant variables for each model

Modeling Scenarios	McFadden pseudo R^2	Number of statistically significant variables
Disregard Road Marking	0.21	4
Distracted by Phone	0.37	9
Distracted by Passenger	0.20	3
Distracted by Outside of Vehicle	0.31	5
Follow too Closely	0.43	11
Improper Overtaking/Passing	0.37	7

McFadden pseudo R^2 statistics across all models were between 0.20 and 0.43, suggesting high statistical fitness. To facilitate explaining modelling results, odds ratios of different scenarios were denoted as follows:

Disregard road marking: $OR_{marking}$

Distracted by phone: OR_{phone}

Distracted by passenger: OR_{pass}

Distracted by outside of vehicle: $OR_{outside}$

Follow too closely: OR_{close}

Improper overtaking/passing: $OR_{overtaking}$

Our findings indicated that compared to single vehicle crashes (such as collision of a vehicle and a fixed object), multiple vehicle crashes are more likely to be hit-and-run crashes. This is probably due to more witness are involved in a multiple vehicle crash and the chance of being caught fleeing is relatively high. In a multiple vehicle crash, if a driver is talking on the phone or distracted by outside of vehicle, he/she would be 45% (OR_{phone} = 1.454) or 57% ($OR_{outside}$ = 1.574) more likely to flee the scene compared to single vehicle crash.

Turning to day of week, drivers are more likely to hit and run during weekends compared to weekdays (OR_{close} = 1.291, $OR_{overtaking}$ = 1.206). This could be partially due to traffic volume is generally lower on weekends compared to weekdays, and driving speed is relatively higher, resulting in more accidents. The result is consistent with previous studies [13,16].

Peak periods are less associated with hit-and-run crashes compared to off-peak periods. For crashes happened during am peak periods, if a driver is distracted by passengers or follows too closely to leading vehicle, he/she is 46% (OR_{pass} = 0.537) or 16% (OR_{close} = 0.842) less like to leave the scene, respectively. On the other hand, during pm peak periods, if a driver follows too closely, he/she is 27% (OR_{close} = 0.733) less likely to flee. This is intuitive, since peak periods are generally associated with heavy traffic and more witnesses, making it relatively difficult to flee without being caught.

Population of area also has significant impact on occurrence of hit-and-run crash. Compared to areas with population over 10,000, crashes within areas of less population are more likely to be hit-and-run crashes. In areas with 2,500 – 5,000 population, the probability of drivers leaving the scene is around 50% higher (OR_{close} = 1.542, $OR_{overtaking}$ = 1.465). And drivers are 43% (OR_{close} = 1.430) more likely to flee in areas with 5,000 – 10,000 population. This implies that drivers feel more confident to flee without being identified in less dense areas.

With regard to crash severity, compared to Property-Damage-Only (PDO) crashes, drivers are more likely to stay when someone is injured. No matter when a driver is talking on the phone (OR_{phone} = 0.409), follows too closely to leading vehicle (OR_{close} = 0.629), or overtakes improperly ($OR_{overtaking}$ = 0.521), he/she tends to stay when someone is injured in the accident. This could be interpreted as fleeing without taking care of injured person might lead to more severe injuries, resulting in serious punishment.

Compared to crashes on rural roads, drivers are less likely to flee on urban roads (ORclose = 0.862). Whereas, it should be noted that crashes on national highway system (NHS) are highly likely to be hit-and-run crashes if the driver is distracted by phone (ORphone = 2.288).

Table. 3 p-value of logistic regression estimation results

Variables	p-Value					
	Disregard Road Marking	Distracted by phone	Distracted by passenger	Distracted by outside of vehicle	Follow too closely	Improper Overtaking/ Passing
Number of vehicles (relative to single vehicle crashes)						
Multiple Vehicle crashes	0.297	0.080	0.324	0.098	0.727	0.671
Day of week (relative to weekdays)						
weekend	0.444	0.697	0.924	0.843	0.000	0.047
Time of day (relative to off-peak periods)						
am peak (7-9)	0.224	0.716	0.034	0.422	0.024	0.479
pm peak (4-6)	0.838	0.953	0.627	0.254	0.000	0.465
Population of area (relative to population over 10,000)						
population (2,500 - 5,000)	0.110	0.754	1.000	0.837	0.003	0.042
population (5,000 – 10,000)	0.287	0.502	0.581	0.312	0.000	0.749
Crash Severity (relative to Property-Damage-Only)						
Injury	0.720	0.022	0.383	0.705	0.000	0.000
Class of trafficway (relative to Rural Roads)						
Urban Road	1.000	0.891	0.781	0.995	0.066	0.379
National highway system (relative to non-NHS)						
NHS	0.731	0.007	0.656	0.592	0.117	0.287
Traffic control device (relative to no control device)						
Traffic signal	0.327	0.004	1.000	0.525	0.121	0.856
Yield	0.000	0.000	0.381	0.304	0.202	0.615
Road surface (relative to dry)						
wet	0.306	0.882	0.000	0.083	0.022	0.062
sand	0.000	0.000	1.000	0.000	1.000	0.000
Crash location (relative to on-pavement)						
work zone	0.594	0.440	1.000	1.000	0.191	0.407
shoulder	0.000	1.000	0.247	1.000	0.482	0.781
Light condition (relative to daylight)						
Darkness	0.000	0.523	0.787	0.796	0.000	0.000
Number of lanes (relative to number of lanes more than 3)						
lanes12	0.851	0.005	0.508	0.038	0.000	0.007
Alignment (relative to flat and straight)						
curve	0.900	0.180	0.381	0.692	0.855	0.621
Median type (relative to not divided roads)						
divided	0.506	0.074	0.000	0.008	0.032	0.832

The presence of traffic control device is more associated with hit-and-run crashes compared to no traffic control device. In particular, crashes on signalized intersection with drivers talking on the phone is highly likely to be hit-and-run crashes (ORphone = 3.751).

Table. 4 Odds Ratio (OR) of logistic regression estimation results

Variables	Odds Ratio (OR)					
	Disregard Road Marking	Distracted by phone	Distracted by passenger	Distracted by outside of vehicle	Follow too closely	Improper Overtaking/ Passing
Number of vehicles (relative to single vehicle crashes)						
Multiple Vehicle crashes	2.294	1.454	1.392	1.574	1.122	1.098
Day of week (relative to weekdays)						
weekend	1.760	0.833	1.045	0.936	1.291	1.206
Time of day (relative to off-peak periods)						
am peak (7-9)	0.220	0.762	0.537	0.693	0.842	1.086
pm peak (4-6)	0.845	0.972	1.456	0.664	0.733	0.932
Population of area (relative to population over 10,000)						
population (2,500 - 5,000)	0.700	0.690	0.000	0.800	1.542	1.465
population (5,000 – 10,000)	3.128	2.221	0.802	1.795	1.430	0.921
Crash Severity (relative to Property-Damage-Only)						
Injury	0.764	0.409	2.514	1.137	0.629	0.521
Class of trafficway (relative to Rural Roads)						
Urban Road	0.560	1.134	0.894	0.996	0.862	0.853
National highway system (relative to non-NHS)						
NHS	0.771	2.288	1.188	1.216	0.915	1.108
Traffic control device (relative to no control device)						
Traffic signal	0.417	3.751	0.000	1.259	1.088	1.018
Yield	1.112	1.231	1.469	3.385	0.389	2.051
Road surface (relative to dry)						
wet	0.293	1.117	0.543	0.441	0.847	0.781
sand	0.614	0.823	0.000	0.551	0.000	1.000
Crash location (relative to on-pavement)						
work zone	2.674	2.679	0.000	0.000	1.245	1.258
shoulder	1.352	0.000	1.495	0.000	0.588	1.295
Light condition (relative to daylight)						
Darkness	2.492	1.325	1.101	0.919	2.080	1.665
Number of lanes (relative to number of lanes more than 3)						
lanes12	1.159	3.934	0.496	1.655	1.384	1.282
Alignment (relative to flat and straight)						
curve	1.187	0.168	0.747	0.731	1.038	1.158
Median type (relative to not divided roads)						
divided	0.639	0.450	0.231	0.590	0.894	0.983

Moreover, crashes on wet and sand road surface are less likely to be hit-and-run crash compared to crashes on dry road surface. Among different scenarios, wet road surface combined with following too closely to leading vehicle produced largest odds ratio (OR_{close} = 0.847).

Driving on road shoulder is prohibited by most transportation authorities unless there is an emergency. Our results indicate drivers are 35% ($OR_{marking}$ = 1.352) more likely to run if the crash is on shoulder and they disregard road marking. This is because they know the accident is caused by their inappropriate behavior. To avoid potential punishment, they tend to flee.

Darkness is highly associate with hit-and-run behaviors compared to sufficient lighting ($OR_{marking}$ = 2.492, OR_{close} = 2.080, $OR_{overtaking}$ = 1.665). Among different scenarios, darkness combined with disregarding road marking produces the largest odds ratio.

Compared to roads with more than 3 lanes, hit-and-run crashes are more likely to happen on roads with 1 or 2 lanes. This is also understandable. More lanes means more traffic and more witnesses, as well as more likely to be caught after fleeing. It should be noted that compared to other improper driving behaviors, drivers distracted by phone have the largest odds ratio (OR_{phone} = 3.934).

Road alignment and median type also affect decisions of hit-and-run. Crashes on curve road are less likely to be hit-and-run crashes compared to straight road (ORphone = 0.168). Divided roads are prone to lower likelihood of hit-and-run crashes compared to non-divided roads (ORphone = 0.450, ORpass = 0.231, ORoutside = 0.590, ORclose = 0.894).

6. Conclusion

Hit-and-run crashes refer to accidents where drivers of striking vehicles directly flee crash scenes without helping victims or reporting accidents to associated authorities. Due to delay of emergency medical assistance, hit-and-run behaviors could significantly increase the likelihood of serious injury and even fatality. In order to reduce the occurrences of hit-and-run crashes, it is crucial to investigate factors contribution to the decision of hit-and-run.

In current study, various factors which might been associated with hit-and-run decisions were taken into account, including number of vehicles, day of week, time of day, population of area, crash severity, class of trafficway, national highway system, traffic control device, road surface, crash location, light condition, number of lanes, alignment and median type. In addition, 6 types of improper driving behaviors at crash scenes were investigated against above variables: i) disregard road marking; ii) distracted by phone; iii) distracted by passenger; iv) distracted by outside of vehicle (people, place or things of interest alongside the road); v) follow too close to the leading vehicle; and vi) improper overtaking/passing.

Logistic regression models were applied to identify factors associated with hit-and-run crashes for different driving behaviors. Police-reported crash data within Cook County in Illinois, USA, between 2004 and 2012 was used to conduct the analysis.

It was found out that variables contributing to hit-and-run crashes varied for different improper driving behaviors. Among 6 different modelling scenarios, "follow too close" and "distracted by phone" had most statistically significant variables. Our study indicated that 11 out of 19 variables were statistically significant for "follow too close" model (weekend, am peak, pm peak, population of 2,500 – 5,000, population of 5,000 – 10,000, injury, urban road, wet surface, darkness, less than three lanes, and divided median). With regard to "distracted by phone" model, 9 out of 19 variables had significant impact on hit-and-run crashes (multiple vehicle crash, injury, national highway system, traffic signal, yield sign, sand surface, less than three lanes, curve alignment and divided median). "Distracted by passenger" model had least number of statistically significant variables (am peak, yield, and divided median).

Following variables would increase the likelihood of hit-and-run crashes in at least one model: multiple vehicle crash, weekend, population of 2,500 – 5,000, population of 5,000 – 10,000, national highway system, traffic signal, yield sign, shoulder, darkness, and less than three lanes. It needs to be pointed out that crashes on less than three lanes involved with drivers talking on the phone had largest odds ratio (ORphone = 3.934).

Findings of current study could offer valuable inputs for reducing hit-and-run crashes in both planning and operation levels. In addition to engineering and law enforcement countermeasures, public education regarding traffic safety and results of hit-and-run crashes is also necessary. The current study could be further enhanced by incorporating more variables in the analysis. Moreover, occurrences of hit-and-run crashes could vary under different traffic and law-enforcing environments. As such, it is also necessary to expand the research based on dataset from other states and countries.

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